The Egyptian Journal of Remote Sensing and Space Sciences (2016) **xxx**, xxx–xxx

HOSTED BY

ELSEVIER

National Authority for Remote Sensing and Space Sciences

The Egyptian Journal of Remote Sensing and Space Sciences

www.elsevier.com/locate/ejrs
www.sciencedirect.com

RESEARCH PAPER

Segmentation based building detection approach from LiDAR point cloud

Anandakumar M. Ramiya [a,*], **Rama Rao Nidamanuri** [a], **Ramakrishan Krishnan** [b]

[a] *Department of Earth and Space Sciences, Indian Institute of Space Science and Technology, Department of Space, Thiruvananthapuram, Kerala, India*
[b] *Amrita Vishwa Vidyapeetham, Coimbatore, India*

Received 19 January 2016; revised 1 April 2016; accepted 4 April 2016

KEYWORDS

LiDAR;
Remote sensing;
Building detection;
Segmentation;
PCL

Abstract Accurate building detection and reconstruction is an important challenge posed to the remote sensing community dealing with LiDAR point cloud. The inherent geometric nature of LiDAR point cloud provides a new dimension to the remote sensing data which can be used to produce accurate 3D building models at relatively less time compared to traditional photogrammetry based 3D reconstruction methods. 3D segmentation is a key step to bring out the implicit geometrical information from the LiDAR point cloud. This research proposes to use open source point cloud library (PCL) for 3D segmentation of LiDAR point cloud and presents a novel histogram based methodology to separate the building clusters from the non building clusters. The proposed methodology has been applied on two different airborne LiDAR datasets acquired over part of urban region around Niagara Falls, Canada and southern Washington, USA. An overall building detection accuracy of 100% and 82% respectively is achieved for the two datasets. The performance of proposed methodology has been compared with the commercially available Terrasolid software. The results show that the buildings detected using open source point cloud library produce comparable results with the buildings detected using commercial software (buildings detection accuracy: 86.3% and 89.2% respectively for the two datasets).

1. Introduction

Realistic 3D city models are gaining prominence with the dynamic growth of urban landscape (Tner, 1999). Various applications in facility management, utility management, disaster management, noise modelling, and city planning (Biljecki et al., 2015; Sun and Salvaggio, 2013; Dadras et al., 2015) substantially benefit from the availability of 3D city models. There is an increase in the demand for street level 3D view of the urban landscape due to the commercial exploitation of 3D geospatial data based products by corporate such as Google and Apple (Anguelov et al., 2010). The traditional photogrammetry based 3D capturing technique, which requires stereo images and extensive processing to create a 3D surface, is being replaced by the rapidly growing LiDAR

* Corresponding author.
E-mail address: ramiya@iist.ac.in (A.M. Ramiya).

Peer review under responsibility of National Authority for Remote Sensing and Space Sciences.

http://dx.doi.org/10.1016/j.ejrs.2016.04.001
1110-9823

Please cite this article in press as: Ramiya, A.M. et al., Segmentation based building detection approach from LiDAR point cloud, Egypt. J. Remote Sensing Space Sci. (2016), http://dx.doi.org/10.1016/j.ejrs.2016.04.001

remote sensing techniques for fast capture of the surface geometry (Baltsavias, 1999; Burtch, 2002). The LiDAR remote sensing is a fast and relatively cost effective means to capture and represent the realistic three dimensional structure of surface objects. LiDAR remote sensing systems record position and elevation of the target points as x, y, z coordinates for representation and storing (Baltsavias, 1999). The LiDAR points are recorded in an unorganized fashion due to the nature of the scan, requiring specific data organization and processing techniques which are significantly different from the existing image processing algorithms. The airborne LiDAR data captured over an urban setting consists of returns from both the natural (trees, bare earth) and man-made features (buildings, cars, roads, etc.). Building features identification and extraction is a key step in urban modelling.

Over the past decade, several algorithms for extraction of buildings from point cloud data have been reported by researchers (Zhang and Lin, 2012; Lari et al., 2011; Wang and Tseng, 2011a; Lafarge and Malllet, 2012). Building extraction from the point cloud involves two sequential steps, namely, filtering, and segmentation. Filtering separates the ground points from non-ground points. There are many well established filtering algorithms available such as morphological filter (Vosselman, 2000), progressive densification filter (Axellson, 2000), surface based filter (Pfeifer, 2005), and segmentation based filter (Filin and Pfeifer, 2006). Morphological filter is based on using structural element which describes the admissible height difference between a ground point and a neighbouring point as a morphological operator to separate the ground and the non-ground points. In case of progressive densification, seed points are chosen to represent the ground points and are triangulated. The ground point set is progressively densified by finding the offset distance and angle of each of the points to the triangulated surface. In contrast to the above filter, surface based filter initially assumes that all the points belong to the ground and then removes non-ground points based on the weights assigned to the points. Segmentation based filter first groups the points into segments using the local normal of each point, computed using the local neighbourhood. Segments are also created using region growing techniques. The segments are then classified into ground and non-ground based on their properties. A review of filtering algorithm by Meng et al. (2010) suggests that most of the filtering algorithms perform well for flat surfaces while producing unacceptable results for undulating terrain.

Segmentation is applied on the non-ground points to detect the various objects present in a scene. Several 3D segmentation algorithms are available to detect landscape features from 3D point cloud. Density based segmentation is based on defining a neighbourhood of radius r and all the points within the sphere of radius r are said to belong to one cluster. Euclidean clustering based segmentation is one of the examples of density based segmentation (Rusu, 2009; Ghosh and Lohani, 2011). Region growing segmentation is based on growing a set of seed points based on the criteria such as global planarity and surface smoothness (Rabbani et al., 2006). Colour based region growing method uses spectral information in addition to the geometrical information for segmentation (Ramiya et al., 2016). Incremental segmentation based on octree structured voxel space is based on establishing neighbourhood of the point cloud followed by coplanar segmentation and co-surface grouping (Wang and Tseng, 2011b). Adaptive segmentation (Lari et al., 2011) is based on defining an adaptive cylinder depending on the point density followed by plane detection. Amongst these algorithms only the density based algorithm can detect both manmade and natural objects in a scene whereas the other algorithms are suitable only for manmade objects (planar objects). For building detection purpose, from the segments created, it is necessary to separate building segments from the non building segments. Limited literature is available on the methods of automatically separating a tree cluster from a building cluster. The existing studies are based on evaluating the fitness of the roof surface points on a plane. The clusters which satisfy these conditions are classified as building segments.

Apart from the key algorithms necessary for processing and analysis, implementation platform such as software platform is a key resource for the effective and affordable analysis of LiDAR point cloud. Commercial LiDAR processing software such as Terrasolid offers routines to automatically detect the building points from the input LiDAR point cloud. However, there is no defined method for automatically extracting buildings from a point cloud besides the lower affordability of commercial software for many researchers. Recently many open source libraries are available to process 3D data. However there is no literature available showcasing the utility of the open source library for building detection. The objective of this work is to develop and validate a building extraction methodology using open source software tool. In this research, an open source point cloud library (PCL) has been used to cluster the entire point cloud data into segments. A novel building detection algorithm is then employed to separate the building clusters from the non building clusters. The buildings extracted using the proposed method are compared with the buildings extracted from a popular commercially LiDAR processing software.

2. Methods and materials

2.1. Filtering

Filtering is an important pre-processing step which separates ground points from the non-ground points thereby reducing the data size and helping in identifying building points. The adopted filtering algorithm belongs to the category of surface based filtering. Each point was given a weight based upon the distance to the mean interpolated surface. A threshold was determined based on the distance of each point from the mean surface. Based on the threshold value, the points are classified either as ground or non-ground point.

2.2. Data structuring

Each point of the LiDAR point cloud is organized in a file in the same pattern of the sensor scan mechanism. In general, the points in LiDAR data are discrete by space and unorganized due to the nature of geometry of the scanning device and target interaction. Hence the LiDAR data do not fit to represent on a grid and have an ill defined boundary hence called as point cloud. Due to this, all the three coordinate values (X, Y, Z) are required for encoding each of the point data. The random point cloud hence becomes more difficult to work with when performing operations such as search or for performing interpolation. We organized the point cloud in a hierarchical data structuring using method kd tree method (Rusu, 2009).

2.3. Segmentation of the point cloud using PCL

3D segmentation of point cloud enables partitioning spatially isolated regions. We implemented the Euclidean distance based segmentation algorithm using PCL (point cloud library) which is an open source VC++ library (Rusu and Cousins, 2011). This segmentation method creates clusters based upon the Euclidean distance between a point and every other point. If the distance is within a particular threshold, the point is placed in a new cluster; otherwise the point is placed in a queue. The process continues until all the points are processed and no point remains in a queue. Minimum and maximum number of points in a cluster is user defined and hence the number of clusters varies for a particular dataset. As mentioned in the previous section, Euclidean distance based segmentation can detect both natural and manmade objects which makes it applicable across many types of landscapes.

2.4. Building cluster detection

To recreate buildings in the scene, the building clusters have to be separated from the clusters of other natural features such as trees. One simple method is to open each of the clusters separately in LiDAR visualization software and separate the building and the non-building cluster. However, this process is cumbersome and time consuming. Automation of this process led to a novel building detection algorithm based on the histogram of the local normal of each point in the clusters. In this method, the local surface normal was computed for each of the points in the cluster. The direction cosines of the normal were found out and histogram was generated. The statistical parameters of the histogram such as mean, range and standard deviation were computed. These parameters vary significantly for a tree cluster from that of a building cluster. This methodology can be adopted to separate building cluster from non-building cluster.

2.5. Building detection using commercial software

Terrasolid is a commercial software capable of end to end processing of LiDAR point cloud. This software uses the progressive densification algorithm for filtering, i.e., separating ground points from non-ground points. The ground points which are identified from the filtering process are used to classify the rest of the points. The non-ground points are labelled into various land cover categories such as low vegetation, high vegetation, buildings based on the distance of the point with respect to the ground points. To detect the set of building points from the non-ground points, the algorithm starts by identifying the holes in the ground points. The non-ground points which are in the location of the holes are checked for planarity conditions. If it satisfies, the points are classified as building points (Soininen, 2015).

3. Experiment on LiDAR datasets

The proposed methodology was implemented using the open source point cloud library in Visual C++ on two different airborne LiDAR datasets which differ by point density and return numbers. The first dataset (dataset 1 in Table 1) was collected in 2004 over the Niagara Falls' neighbourhood using the Airborne Laser Terrain Mapping (ALTM) 3100 sensor (Optech Inc., Concord, Canada) at a flying height of 1190 m.

Table 1 Airborne LiDAR datasets used for the study.

Parameters/dataset	Dataset 1	Dataset 2
Pt density (pts/sq m)	2	5.5
Number of 1 return	31,033	108,198
Number of 2 return	2594	0
Number of 3 return	76	0
Number of 4 return	0	0
Total number of points	33,703	108,198
x range	112	103
y range	139	201

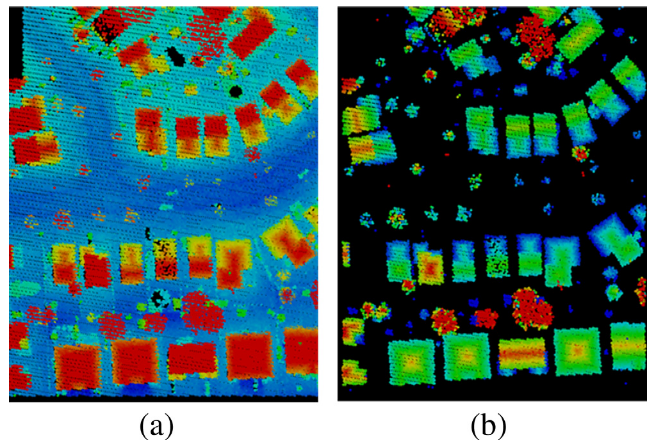


Figure 1 Before and after filtering: (a) dataset 1 before filtering, (b) non-ground points from dataset 1.

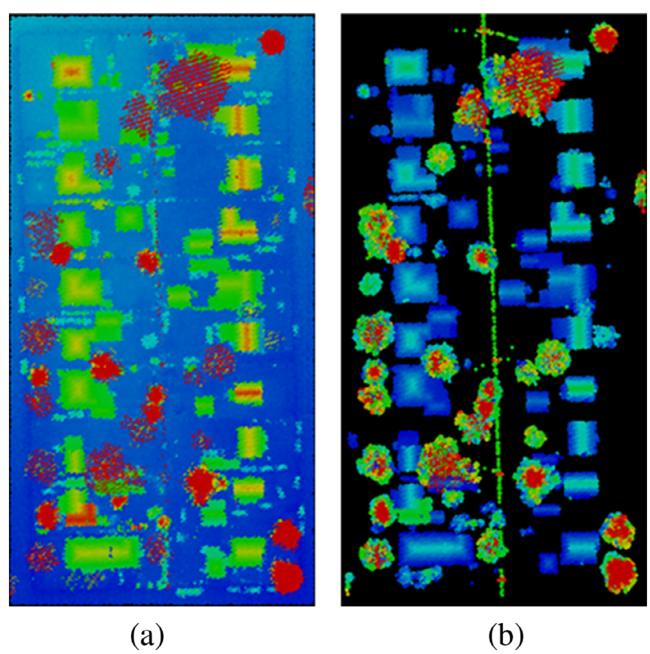


Figure 2 Before and after filtering: (a) dataset 2 before filtering, (b) non-ground points from dataset 2.

Please cite this article in press as: Ramiya, A.M. et al., Segmentation based building detection approach from LiDAR point cloud, Egypt. J. Remote Sensing Space Sci. (2016), http://dx.doi.org/10.1016/j.ejrs.2016.04.001

Table 2 Number of points before and after filtering.

Parameters	LiDAR dataset	
	Dataset 1	Dataset 2
Total number of points	33,703	108,198
Ground point	22,645	72,478
Non-ground point	11,058	35,720

The density of the data is 2 points/sq m. The second dataset (dataset 2 in Table 1) was part of the LiDAR data collected in 2005 over the Yakima county of southern Washington using the Terrapoint-s40 ALTMS flying at a height of 1060 m. The density of the data is 5.5 points/sq m.

4. Results and discussion

Figs. 1 and 2 show the output after filtering of both LiDAR datasets. The ground points are effectively removed from the point cloud (see Figs. 1 and 2). Table 2 shows the details of points before and after filtering. The filtered dataset was arranged using kd tree structuring. The points were then segmented into different clusters by 3D Euclidean distance based segmentation. From the clusters obtained, building and non building clusters were separated using the histogram of the local surface normal of each cluster.

Each of the clusters obtained for the dataset was categorized into building and non-building cluster based on the peaks of the respective histogram. Fig. 3 shows the histogram of the non-building cluster. The range and mean of the values of the elements in the histogram can be used to separate a building cluster from a non-building cluster. As seen in Fig. 3, the histograms derived from the building clusters exhibit few distinct peaks whereas the histogram of the non-building clusters spread wide apart. For dataset 1, 35 clusters were identified. Some of the user defined parameters included minimum and maximum number of points in the clusters. In this case, the minimum cluster size was 50 and maximum cluster size was 5000. Visual inspection of the dataset 1 indicates that there are 25 buildings and 3 trees. The method implemented in this work identified 25 buildings as can be seen in Fig. 4.

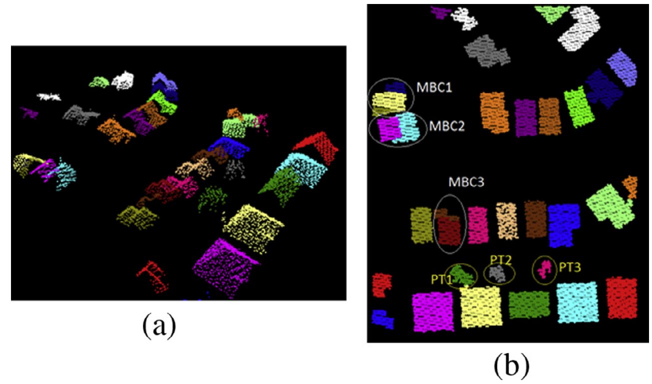


Figure 4 Result of Euclidean based segmentation (a) top view of building clusters for dataset 1 (b) building clusters for dataset 1.

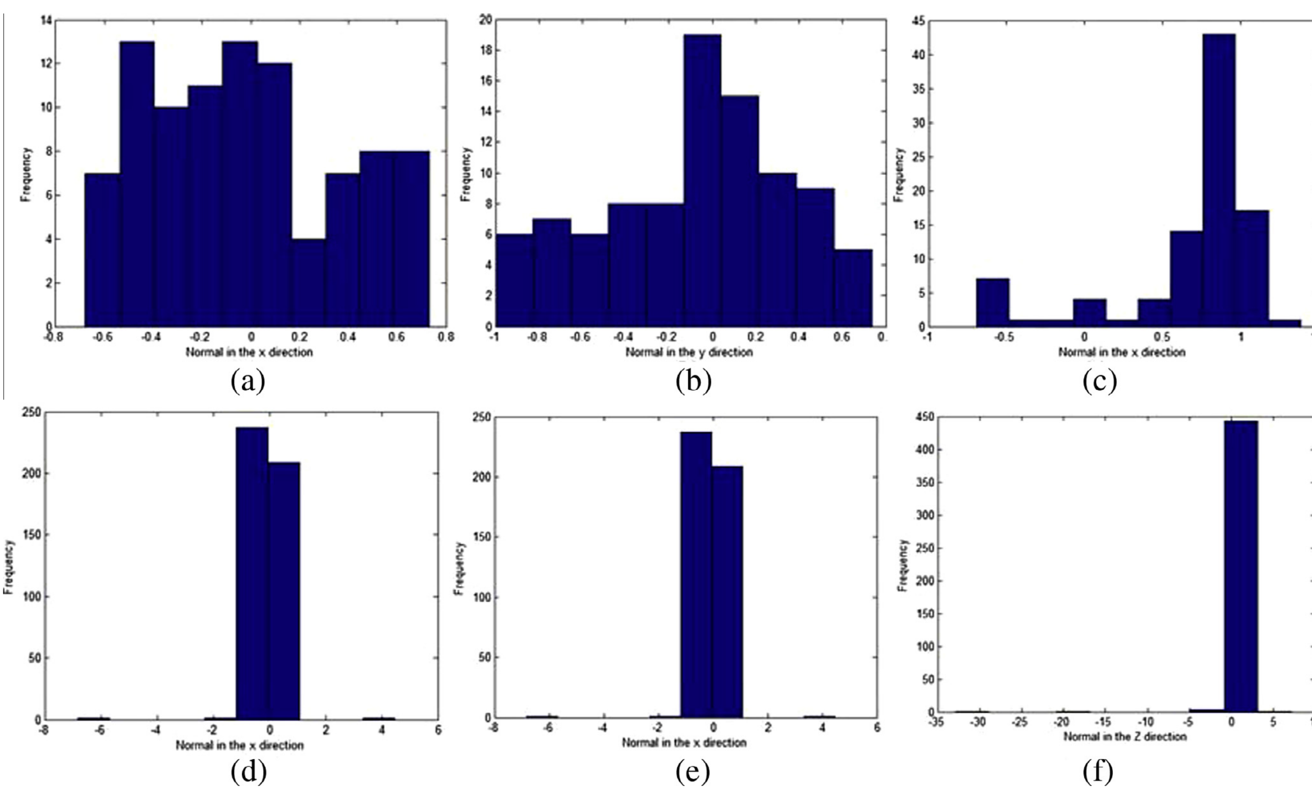
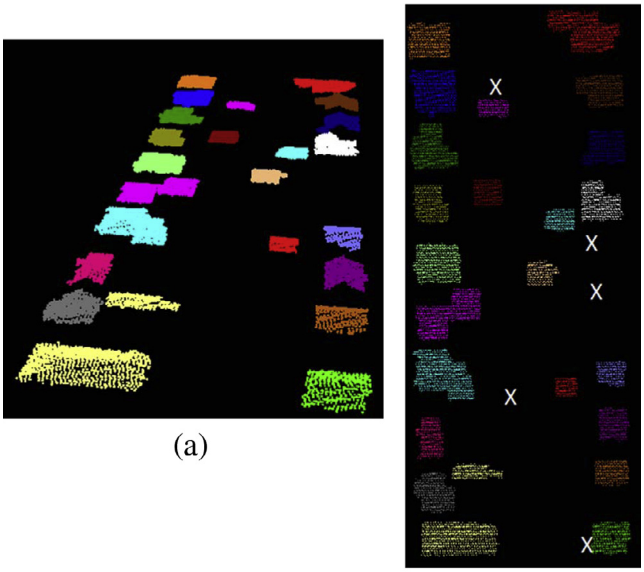


Figure 3 Histogram of the surface normal of a building cluster and a non-building cluster (a) histogram of surface normal of tree in the *x* direction, (b) histogram of surface normal of tree in the y direction, (c) histogram of surface normal of tree in the *z* direction, (d) histogram of surface normal of building in the x direction; (e) histogram of surface normal of building in the *y* direction, (f) histogram of surface normal of building in the z direction.

Please cite this article in press as: Ramiya, A.M. et al., Segmentation based building detection approach from LiDAR point cloud, Egypt. J. Remote Sensing Space Sci. (2016), http://dx.doi.org/10.1016/j.ejrs.2016.04.001



(a) (b)

Figure 5 Result of Euclidean based segmentation: (a) top view of building clusters for dataset 2 (b) building clusters for dataset 2.

Table 3 Results of Euclidean based segmentation.

Parameters	LiDAR dataset	
	Dataset 1	Dataset 2
Cluster tolerance (*d*th)	1 m	0.75 m
Min/max number of points in the cluster	50–5000	200–1200
Non-ground point	11,058	35,720
No. of clusters	35	24
No. of buildings in the survey area	25	25
No. of buildings identified in the survey area	25	24

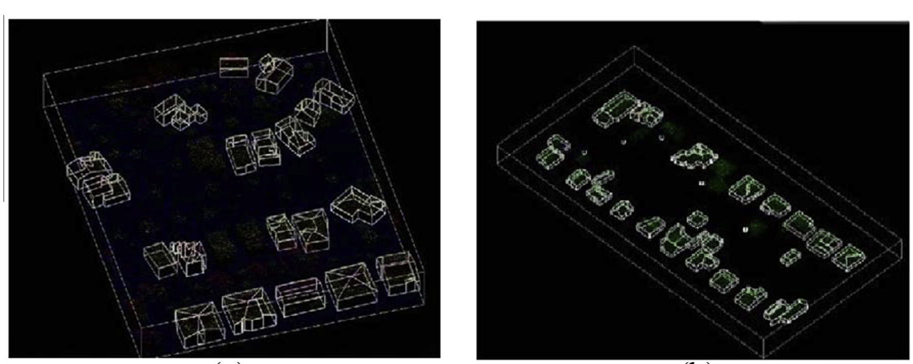
Although all the buildings are identified by the segmentation process, some buildings were segmented as multiple clusters. The mark 'MBC' represents the multiple building clusters. One reason which can be attributed to this is the presence of multiple roofs for the building at different heights. These partial buildings must be merged together while creating the final output for 3D model of the building. All the three tree clusters are identified using the clustering algorithm. However, only the partial tree clusters are identified. Buildings which are classified under multiple clusters are marked using MC1, MC2, and MC3. In total, all 25 building clusters including the multiple building clusters are identified in dataset 1.

For dataset 2, 24 clusters were identified. The minimum and maximum number of clusters set chosen is 200 and 1200. For this dataset, there are no multiple clusters or the presence of tree clusters. Manual inspection indicates the presence of 28 buildings in dataset 2 of which 23 building clusters are identified (Fig. 5). Table 3 summarizes the results of Euclidean based clustering on dataset 1 and dataset 2. The choice of minimum and maximum number of points in the cluster is to minimize the over-segmentation and under-segmentation of the cluster.

4.1. Comparison with the buildings identified using Terrasolid software

For dataset 1, out of the total 33,703 points, 22,243 points were classified as non-ground points. For dataset 2, out of the total 108,198 points, 69,992 points were classified as ground points (Fig. 4). Building detection algorithm in the Terrasolid software is based on the fitting plane to a set of points which are initially identified based on the holes created identified in the ground points as discussed in Section 2.5. User defined parameters such as the smallest size of the building footprint, tolerance value i.e., the minimum elevation difference of a point from the plane fitted, determine the building points. In this study, the parameters were set based on heuristic method. The results of building modelling using Terrasolid are given in Fig. 6.

A comparison of the results of the buildings modelled using Euclidean clustering based segmentation algorithm in the open source library PCL and Terrascan software algorithm is given in Tables 4 and 5. As evident from Tables 4 and 5, the performance of building extraction is comparable. In dataset 1, all the 25 buildings are identified by the Euclidean clustering based segmentation algorithm whereas the commercial software is able to identify only 19 buildings. This can be attributed to the failure in the detection of planar patches amongst the detected building points. In dataset 2, the commercial software outperformed the Euclidean clustering based segmentation in identifying the buildings. Five building clusters marked as 'U' are not identified as building points. The missing building patches are those which have less number of



(a) (b)

Figure 6 Result of building detection by Terrasolid (a) dataset 1, (b) dataset 2.

Table 4 Comparison of the buildings extracted by the proposed EC segmentation based methodology with the Terrasolid software based results for dataset 1.

Parameters	By EC segmentation	Terrasolid
Non-ground points	11,016	11,460
Building points	6433	5191
No of buildings in the surveyed area	25	25
No. of buildings identified	25	19
No. of buildings modelled	24	25
False positives	0	0
True negatives	0	0
Modelling accuracy	100 (%)	86.3 (%)

Table 5 Comparison of the buildings extracted by the proposed EC segmentation based methodology with the Terrasolid software based results for dataset 2.

Parameters	By EC segmentation	Terrasolid
Non-ground points	35,720	38,206
Building points	13,676	15,966
No of buildings in the surveyed area	28	28
No. of buildings identified	23	25
No. of buildings modelled	23	20
False positives	0	0
True negatives	5	5
Modelling accuracy	82 (%)	89.2 (%)

points than the minimum threshold value in the Euclidean clustering based segmentation. The minimum cluster value was set to avoid over segmentation of the building objects. From the experiments, it is evident that the choice of the user defined parameters influences substantially the building clusters detected. In spite of these limitations, it is evident that the building clusters detected using the proposed histogram based method in open source implementation is comparable with the commercial software. This observation signifies the functional utility of the open source point cloud library to effectively implement building detection and modelling using LiDAR point data, besides affordability. More studies are recommended for automatically determining the user defined parameters based on point density of the point cloud for improving the building detection.

5. Conclusions

This study presents a novel data driven methodology for building detection using the open source point cloud library. The point cloud data were segmented in 3D using Euclidean distance based segmentation methods. From the segments created the building clusters are separated from the non-building clusters by a novel histogram based method. The performance of the proposed methodology has been compared with the automatic building detection routine available in a popular commercial LiDAR data processing software (Terrasolid). The performance of the proposed methodology is comparable to that of the commercial version. Overall their accuracies are 100%, 82% and 86.3%, 89.2% respectively from the two different implementations. Further, it has been observed that the performance of the proposed methodology does not depend on the point cloud density. A major limitation of the study is that analyst needs to specify the minimum and maximum number of points in a cluster. This makes the procedure a semi automatic process. Further works are recommended to refine this method to automatically select the minimum and maximum number of points in the clusters based on the dataset.

Conflict of interest

There is no conflict of interest.

Acknowledgements

The authors also acknowledge Terrasolid Ltd. and NOAA Coastal Services Center for providing the LiDAR data used in this work.

References

Anguelov, Dragomir, Dulong, Carole, Filip, Daniel, Frueh, Christian, Lafon, Stéphane, Lyon, Richard, Ogale, Abhijit, Vincent, Luc, Weaver, Josh, 2010. Google street view: capturing the world at street level. Computer 43 (6), 32–38.

Axellson, P., 2000. DEM generation from laser scanner data using adaptive TIN models. In: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XXXIII, pp. 110–117.

Baltsavias, E.P., 1999. Airborne laser scanning: basic relations and formulas. ISPRS J. Photogramm. Remote Sens. 54 (2–3), 199–214.

Biljecki, Filip, Stoter, Jantien, Ledoux, Hugo, Zlatanova, Sisi, Çöltekin, Arzu, 2015. Applications of 3D city models: state of the art review. ISPRS Int. J. Geo-Inf. 4 (4), 2842–2889.

Burtch, Robert, 2002. Lidar principles and applications. In: IMAGIN Conference, pp. 1–13.

Dadras, Mohsen, Shafri, Helmi Z.M., Ahmad, Noordin, Pradhan, Biswajeet, Safarpour, Sahabeh, 2015. Spatio-temporal analysis of urban growth from remote sensing data in Bandar Abbas City, Iran. Egypt. J. Remote Sens. Space Sci. 18 (1), 35–52.

Filin, S., Pfeifer, N., 2006. Segmentation of airborne laser scanning data using slope adaptive neighbourhood. ISPRS J. Photogramm. Remote Sens.

Ghosh, S., Lohani, B., 2011. Heuristical feature extraction from LiDAR data and their visualization. In: Proceedings of the ISPRS Workshop on Laser Scanning.

Lafarge, Florent, Malllet, Clement, 2012. Creating large-scale city models from 3D-point clouds: a robust approach with hybrid representation. Int. J. Comput. Vision 1, 69–85.

Lari, Z., Habib, A., Kwak, E., 2011. An adaptive approach for segmentation of 3D laser point cloud. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, pp. 103–108 (XXXVIII-5).

Meng, X., Currit, N., Zhao, K., 2010. Ground filtering algorithms for airborne LiDAR data: a review of critical issues. Remote Sens.

Pfeifer, N., 2005. A subdivision algorithm for smooth 3D terrain models. ISPRS J. Photogramm. Remote Sens.

Rabbani, T.F., Heuvel, V.D., Vosselmann, G., 2006. Egmentation of point clouds using smoothness constraints. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, pp. 248–253.

Ramiya, Anandakumar M., Nidamanuri, Rama Rao, Krishnan, Ramakrishnan, 2016. Object-oriented semantic labelling of spec-

tral–spatial LiDAR point cloud for urban land cover classification and buildings detection. Geocarto Int. 31 (2).
Rusu, R.B., 2009. Semantic 3D Object Maps for Everyday Manipulation in Human Living Environments. Computer Science Dept, Technische Universit, Munchen, Germany.
Rusu, Radu Bogdan, Cousins, Steve, 2011. 3D is here: Point Cloud Library (PCL). In: 2011 IEEE International Conference on Robotics and Automation (May), pp. 1–4.
Soininen Arttu, 2015. TerraScan User's Guide.
Sun, Shaosui, Salvaggio, Carl, 2013. Aerial 3D building detection and modeling from airborne LiDAR point clouds. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.
Tner, Wolfgang Förs, 1999. 3D-city models: automatic and semiautomatic acquisition methods. Computing, 291–303.
Vosselman, P., 2000. Slope based filtering of laser altimetric data. In: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XXXIII.
Wang, M., Tseng, Y.H., 2011a. Incremental segmentation of lidar point clouds with an octree-structured voxel space. Photogramm. Rec.
Wang, Miao, Yi-Hsing, Tseng, 2011b. Incremental segmentation of lidar point clouds with an octree-structured voxel space. Photogramm. Rec. 26 (133), 32–57 (March 16).
Zhang, J.X., Lin, X.G., 2012. Object-based classification of urban airborne lidar point clouds with multiple echoes using SVM. ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences I (September), 135–140.

Please cite this article in press as: Ramiya, A.M. et al., Segmentation based building detection approach from LiDAR point cloud, Egypt. J. Remote Sensing Space Sci. (2016), http://dx.doi.org/10.1016/j.ejrs.2016.04.001